

# Unified View of Matrix Completion under General Structural Constraints

**Suriya Gunasekar**

SURIYA@UTEXAS.EDU

**Arindam Banerjee**

BANERJEE@CS.UMN.EDU

**Joydeep Ghosh**

GHOSH@ECE.UTEXAS.EDU

## Abstract

In this paper, we present a unified analysis of matrix completion under general low-dimensional structural constraints induced by *any* norm regularization. We consider two estimators for the general problem of structured matrix completion, and provide unified upper bounds on the sample complexity and the estimation error. Our analysis relies on results from generic chaining, and we establish two intermediate results of independent interest: (a) in characterizing the size or complexity of low dimensional subsets in high dimensional ambient space, a certain *partial* complexity measure encountered in the analysis of matrix completion problems is characterized in terms of a well understood complexity measure of Gaussian widths, and (b) it is shown that a form of restricted strong convexity holds for matrix completion problems under general norm regularization. Further, we provide several non-trivial examples of structures included in our framework, notably the recently proposed spectral  $k$ -support norm.

## 1. Introduction

The task of completing the missing entries of a matrix from an incomplete subset of (potentially noisy) entries is encountered in many applications including recommendation systems, data imputation, covariance matrix estimation, and sensor localization among others. High dimensional estimation problems, where the number of parameters to be estimated is much higher than the number of observations are traditionally ill-posed. However, under low dimensional structural constraints, such problems have been extensively studied in the recent literature. The special case of matrix completion problems are particularly ill-posed as the observations are both limited (high dimensional), and the measurements are extremely localized, i.e., the observations consist of individual matrix entries. The localized measurement model, in contrast to random Gaussian or sub-Gaussian measurements, poses additional complications in high dimensional estimation.

For well-posed estimation in high dimensional problems, including matrix completion, it is imperative that low dimensional structural constraints are imposed on the target. For matrix completion, the special case of low-rank constraint has been widely studied. Several existing work propose tractable estimators with near-optimal recovery guarantees for (approximate) low-rank matrix completion (Candés and Recht, 2009; Candés and Plan, 2010; Recht, 2011; Negahban and Wainwright, 2012; Keshavan et al., 2010a,b; Koltchinskii et al., 2011; Davenport et al., 2014; Klopp, 2014, 2015). A recent work Gunasekar et al. (2014) addresses the extension to structures with decomposable

norm regularization. However, the scope of matrix completion extends for low dimensional structures far beyond simple low-rankness or decomposable norm structures.

In this paper, we present a unified statistical analysis of matrix completion under general low dimensional structures that are induced by *any* suitable norm regularization. We provide statistical analysis of two generalized matrix completion estimators, the *constrained norm minimizer*, and the *generalized matrix Dantzig selector* (Section 2.2). The main results in the paper (Theorem 1a–1b) provide unified upper bounds on the sample complexity and estimation error of these estimators for matrix completion under *any* norm regularization. Existing results on matrix completion with low rank or other decomposable structures can be obtained as special cases of Theorem 1a–1b.

Our unified analysis of sample complexity is motivated by recent work on high dimensional estimation using global (sub) Gaussian measurements Chandrasekaran et al. (2012); Amelunxen et al. (2014); Tropp (2014); Banerjee et al. (2014); Vershynin (2014); Cai et al. (2014). A key ingredient in the recovery analysis of high dimensional estimation involves establishing some variation of a certain Restricted Isometry Property (RIP) Candes and Tao (2005) of the measurement operator. It has been shown that such properties are satisfied by Gaussian and sub-Gaussian measurement operators with high probability. Unfortunately, as has been noted before by Candes et al. Candés and Recht (2009), owing to highly localized measurements, such conditions are not satisfied in the matrix completion problem, and the existing results based on global (sub) Gaussian measurements are not directly applicable. In fact, one of the questions we address is: given the radically limited measurement model in matrix completion, by how much would the sample complexity of estimation increase beyond the known sample complexity bounds for global (sub) Gaussian measurements? Our results upper bound the sample complexity for matrix completion to within a  $\log d$  factor over that for estimation under global (sub) Gaussian measurements Chandrasekaran et al. (2012); Banerjee et al. (2014); Cai et al. (2014). While the result was previously known for low rank matrix completion using nuclear norm minimization Negahban and Wainwright (2012); Klopp (2014), with a careful use of generic chaining, we show that the  $\log d$  factor suffices for structures induced by *any* norm! As a key intermediate result, we show that a useful form of *restricted strong convexity* (RSC) Negahban et al. (2009) holds for the localized measurements encountered in matrix completion under general norm regularized structures. The result substantially generalizes existing RSC results for matrix completion under the special cases of nuclear norm and decomposable norm regularization Negahban and Wainwright (2012); Gunasekar et al. (2014).

For our analysis, we use tools from generic chaining Talagrand (2014) to characterize the main results (Theorem 1a–1b) in terms of the *Gaussian width* (Definition 1) of certain *error sets*. Gaussian widths provide a powerful geometric characterization for quantifying the complexity of a structured low dimensional subset in a high dimensional ambient space. Numerous tools have been developed in the literature for bounding the Gaussian width of structured sets. A unified characterization of results in terms of Gaussian width has the advantage that this literature can be readily leveraged to derive new recovery guarantees for matrix completion under suitable structural constraints (Appendix D.2).

In addition to the theoretical elegance of such a unified framework, identifying useful but potentially non-decomposable low dimensional structures is of significant practical interest. The broad class of structures enforced through symmetric convex bodies and symmetric atomic sets (Chandrasekaran et al., 2012) can be analyzed under this paradigm (Section 2.1). Such specialized structures can capture the constraints in certain applications better than simple low-rankness. In

particular, we discuss in detail, a non-trivial example of the *spectral  $k$ -support norm* introduced by McDonald et al. McDonald et al. (2014).

To summarize the key contributions of the paper:

- Theorem 1a–1b provide unified upper bounds on sample complexity and estimation error for matrix completion estimators using general norm regularization: a substantial generalization of the existing results on matrix completion under structural constraints.
- Theorem 1a is applied to derive statistical results for the special case of matrix completion under spectral  $k$ -support norm regularization.
- An intermediate result, Theorem 5 shows that under any norm regularization, a variant of Restricted Strong Convexity (RSC) holds in the matrix completion setting with extremely localized measurements. Further, a certain *partial* measure of complexity of a set is encountered in matrix completion analysis (12). Another intermediate result, Theorem 2 provides bounds on the *partial* complexity measures in terms of a better understood complexity measure of Gaussian width. These intermediate results are of independent interest beyond the scope of the paper.

### Notations and Preliminaries

Indexes  $i, j$  are typically used to index rows and columns respectively of matrices, and index  $k$  is used to index the observations.  $e_i, e_j, e_k$ , etc. denote the standard basis in appropriate dimensions\*. Notation  $G$  and  $g$  are used to denote a matrix and vector respectively, with independent standard Gaussian random variables.  $\mathbb{P}(\cdot)$  and  $\mathbb{E}(\cdot)$  denote the probability of an event and the expectation of a random variable, respectively. Given an integer  $N$ , let  $[N] = \{1, 2, \dots, N\}$ . Euclidean norm in a vector space is denoted as  $\|x\|_2 = \sqrt{\langle x, x \rangle}$ . For a matrix  $X$  with singular values  $\sigma_1 \geq \sigma_2 \geq \dots$ , common norms include the *Frobenius norm*  $\|X\|_F = \sqrt{\sum_i \sigma_i^2}$ , the *nuclear norm*  $\|X\|_* = \sum_i \sigma_i$ , the *spectral norm*  $\|X\|_{\text{op}} = \sigma_1$ , and the *maximum norm*  $\|X\|_\infty = \max_{ij} |X_{ij}|$ . Also let,  $\mathbb{S}^{d_1 d_2 - 1} = \{X \in \mathbb{R}^{d_1 \times d_2} : \|X\|_F = 1\}$  and  $\mathbb{B}^{d_1 d_2} = \{X \in \mathbb{R}^{d_1 \times d_2} : \|X\|_F \leq 1\}$ . Finally, given a norm  $\mathcal{R}(\cdot)$  defined on a vectorspace  $\mathcal{V}$ , its *dual norm* is given by  $\mathcal{R}^*(X) = \sup_{\mathcal{R}(Y) \leq 1} \langle X, Y \rangle$ .

**Definition 1** (Gaussian Width). Gaussian width of a set  $S \subset \mathbb{R}^{d_1 \times d_2}$  is a widely studied measure of complexity of a subset in high dimensional ambient space and is given by:

$$w_G(S) = \mathbb{E}_G \sup_{X \in S} \langle X, G \rangle, \quad (1)$$

where recall that  $G$  is a matrix of independent standard Gaussian random variables. Some key results on Gaussian width are discussed in Appendix D.2.

**Definition 2** (Sub-Gaussian Random Variable Vershynin (2012)). The sub-Gaussian norm of a random variable  $X$  is given by:  $\|X\|_{\Psi_2} = \sup_{p \geq 1} p^{-1/2} (\mathbb{E}|X|^p)^{1/p}$ .  $X$  is *b-sub-Gaussian* if  $\|X\|_{\Psi_2} \leq b < \infty$ .

Equivalently,  $X$  is sub-Gaussian if one of the following conditions are satisfied for some constants  $k_1, k_2$ , and  $k_3$  [Lemma 5.5 of Vershynin (2012)].

- (1)  $\forall p \geq 1, (\mathbb{E}|X|^p)^{1/p} \leq b\sqrt{p},$       (2)  $\forall t > 0, \mathbb{P}(|X| > t) \leq e^{1-t^2/k_1^2 b^2},$
- (3)  $\mathbb{E}[e^{k_2 X^2/b^2}] \leq e$ , or      (4) if  $\mathbb{E}X = 0$ , then  $\forall s > 0, \mathbb{E}[e^{sX}] \leq e^{k_3 s^2 b^2/2}.$

**Definition 3** (Restricted Strong Convexity (RSC)). A function  $\mathcal{L}$  is said to satisfy *Restricted Strong Convexity (RSC)* at  $\Theta$  with respect to a subset  $S$ , if for some *RSC parameter*  $\kappa_{\mathcal{L}} > 0$ ,

$$\forall \Delta \in S, \mathcal{L}(\Theta + \Delta) - \mathcal{L}(\Theta) - \langle \nabla \mathcal{L}(\Theta), \Delta \rangle \geq \kappa_{\mathcal{L}} \|\Delta\|_F^2. \quad (2)$$

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\*for brevity we omit the explicit dependence of dimension unless necessary

**Definition 4** (Spikiness Ratio Negahban and Wainwright (2012)). For  $X \in \mathbb{R}^{d_1 \times d_2}$ , a measure of its “spikiness” is given by:

$$\alpha_{\text{sp}}(X) = \frac{\sqrt{d_1 d_2} \|X\|_\infty}{\|X\|_F}. \quad (3)$$

**Definition 5** (Norm Compatibility Constant (Negahban et al., 2009)). The compatibility constant of a norm  $\mathcal{R} : \mathcal{V} \rightarrow \mathbb{R}$  under a closed convex cone  $\mathcal{C} \subset \mathcal{V}$  is defined as follows:

$$\Psi_{\mathcal{R}}(\mathcal{C}) = \sup_{X \in \mathcal{C} \setminus \{0\}} \frac{\mathcal{R}(X)}{\|X\|_F}. \quad (4)$$

## 2. Structured Matrix Completion

Denote the ground truth target matrix as  $\Theta^* \in \mathbb{R}^{d_1 \times d_2}$ ; let  $d = d_1 + d_2$ . In the noisy matrix completion, observations consists of individual entries of  $\Theta^*$  observed through an additive noise channel.

**Sub-Gaussian Noise:** Given, a list of independently sampled standard basis  $\Omega = \{E_k = e_{i_k} e_{j_k}^\top : i_k \in [d_1], j_k \in [d_2]\}$  with potential duplicates, observations  $(y_k)_k \in \mathbb{R}^{|\Omega|}$  are given by:

$$y_k = \langle \Theta^*, E_k \rangle + \xi \eta_k, \text{ for } k = 1, 2, \dots, |\Omega|, \quad (5)$$

where  $\eta \in \mathbb{R}^{|\Omega|}$  is the noise vector of independent sub-Gaussian random variables with  $\mathbb{E}[\eta_k] = 0$  and  $\text{Var}(\eta_k) = 1$ , and  $\xi^2$  is scaled variance of noise per observation. Further let  $\|\eta_k\|_{\Psi_2} \leq b$  for a constant  $b$  (recall  $\|\cdot\|_{\Psi_2}$  from Definition 2). Also, without loss of generality, assume normalization  $\|\Theta^*\|_F = 1$ .

**Uniform Sampling:** Assume that the entries in  $\Omega$  are drawn independently and uniformly:

$$E_k \sim \text{uniform}\{e_i e_j^\top : i \in [d_1], j \in [d_2]\}, \text{ for } E_k \in \Omega. \quad (6)$$

Let  $\{e_k\}$  be the standard basis of  $\mathbb{R}^{|\Omega|}$ . Given  $\Omega$ , define  $P_\Omega : \mathbb{R}^{d_1 \times d_2} \rightarrow \mathbb{R}^{|\Omega|}$  as:

$$P_\Omega(X) = \sum_{k=1}^{|\Omega|} \langle X, E_k \rangle e_k \quad (7)$$

**Structural Constraints** For matrix completion with  $|\Omega| < d_1 d_2$ , low dimensional structural constraints on  $\Theta^*$  are necessary for well-posedness. We consider a generalized constraint setting wherein for some low-dimensional *model space*  $\mathcal{M}$ ,  $\Theta^* \in \mathcal{M}$  is enforced through a surrogate *norm regularizer*  $\mathcal{R}(\cdot)$ . We make no further assumptions on  $\mathcal{R}$  other than it being a norm in  $\mathbb{R}^{d_1 \times d_2}$ .

**Low Spikiness** In matrix completion under uniform sampling model, further restrictions on  $\Theta^*$  (beyond low dimensional structure) are required to ensure that the most informative entries of the matrix are observed with high probability (Candés and Recht, 2009). Early work assumed stringent matrix incoherence conditions for low-rank completion to preclude such matrices (Candés and Plan, 2010; Keshavan et al., 2010a,b), while more recent work (Davenport et al., 2014; Negahban and Wainwright, 2012), relax these assumptions to a more intuitive restriction of the spikiness ratio, defined in (3). However, under this relaxation only an approximate recovery is typically guaranteed in low-noise regime, as opposed to near exact recovery under incoherence assumptions Negahban and Wainwright (2012); Davenport et al. (2014).

**Assumption 1** (Spikiness Ratio). *There exists  $\alpha^* > 0$ , such that*

$$\|\Theta^*\|_\infty = \alpha_{\text{sp}}(\Theta^*) \frac{\|\Theta^*\|_F}{\sqrt{d_1 d_2}} \leq \frac{\alpha^*}{\sqrt{d_1 d_2}}. \quad \square$$

## 2.1 Special Cases and Applications

We briefly introduce some interesting examples of structural constraints with practical applications.

**Example 1** (Low Rank and Decomposable Norms). *Low-rankness* is the most common structure used in many matrix estimation problems including collaborative filtering, PCA, spectral clustering, etc. Convex estimators using nuclear norm  $\|\Theta\|_*$  regularization has been widely studied statistically (Candés and Recht, 2009; Candés and Plan, 2010; Recht, 2011; Negahban and Wainwright, 2012; Keshavan et al., 2010a,b; Koltchinskii et al., 2011; Davenport et al., 2014; Klopp, 2014, 2015). A recent work Gunasekar et al. (2014) extends the analysis of matrix completion to general decomposable norms: norms  $\mathcal{R}$ , such that  $\forall X, Y \in (\mathcal{M}, \mathcal{M}^\perp), \mathcal{R}(X+Y) = \mathcal{R}(X) + \mathcal{R}(Y)$ .

**Example 2** (Spectral  $k$ -support Norm). A non-trivial and significant example of norm regularization that is not decomposable is the *spectral  $k$ -support* norm recently introduced by McDonald et al. McDonald et al. (2014). Spectral  $k$ -support norm is essentially the vector  $k$ -support norm (Argyriou et al., 2012) applied on the singular values  $\sigma(\Theta)$  of a matrix  $\Theta \in \mathbb{R}^{d_1 \times d_2}$ . Without loss of generality, let  $\bar{d} = d_1 = d_2$ .

Let  $\mathcal{G}_k = \{g \subseteq [\bar{d}] : |g| \leq k\}$  be the set of all subsets  $[d]$  of cardinality at most  $k$ , and let  $\mathcal{V}(\mathcal{G}_k) = \{(v_g)_{g \in \mathcal{G}_k} : v_g \in \mathbb{R}^{\bar{d}}, \text{supp}(v_g) \subseteq g\}$ . The spectral  $k$ -support norm is given by:

$$\|\Theta\|_{k\text{-sp}} = \inf_{v \in \mathcal{V}(\mathcal{G}_k)} \left\{ \sum_{g \in \mathcal{G}_k} \|v_g\|_2 : \sum_{g \in \mathcal{G}_k} v_g = \sigma(\Theta) \right\}, \quad (8)$$

McDonald et al. McDonald et al. (2014) showed that spectral  $k$ -support norm is a special case of *cluster norm* Jacob et al. (2009). It was further shown that in multi-task learning, wherein the tasks (columns of  $\Theta^*$ ) are assumed to be clustered into dense groups, the cluster norm provides a trade-off between intra-cluster variance, (inverse) inter-cluster variance, and the norm of the task vectors. Both Jacob et al. (2009) and McDonald et al. (2014) demonstrate superior empirical performance of cluster norms (and  $k$ -support norm) over traditional trace norm and spectral elastic net minimization on bench marked matrix completion and multi-task learning datasets. However, statistical analysis of consistent matrix completion using spectral  $k$ -support norm regularization has not been previously studied. In Section 3.2, we discuss the consequence of our main theorem for this non-trivial special case.

**Example 3** (Additive Decomposition). Elementwise sparsity is a common structure often assumed in high-dimensional estimation problems. However, in matrix completion, elementwise sparsity conflicts with Assumption 1 (and more traditional incoherence assumptions). Indeed, it is easy to see that with high probability most of the  $|\Omega| \ll d_1 d_2$  uniformly sampled observations will be zero, and an informed prediction is infeasible. However, elementwise sparse structures can often be modelled within an *additive decomposition* framework, wherein  $\Theta^* = \sum_k \Theta^{(k)}$ , such that each component matrix  $\Theta^{(k)}$  is in turn structured (e.g. low rank+sparse used for robust PCA Candés et al. (2011)). In such structures, there is no scope for recovering sparse components outside the observed indices, and it is assumed that:  $\Theta^{(k)}$  is sparse  $\Rightarrow \text{supp}(\Theta^{(k)}) \subseteq \Omega$ . In such cases, our results are applicable under additional regularity assumptions that enforces non-spikiness on the superposed matrix. A candidate norm regularizer for such structures is the weighted infimum convolution of individual structure inducing norms (Candés et al., 2011; Yang and Ravikumar, 2013),

$$\mathcal{R}_w(\Theta) = \inf \left\{ \sum_k w_k \mathcal{R}_k(\Theta^{(k)}) : \sum_k \Theta^{(k)} = \Theta \right\}.$$

**Example 4** (Other Applications). Other potential applications including *cut matrices* (Srebro and Shraibman, 2005; Chandrasekaran et al., 2012), structures induced by *compact convex sets*, norms inducing *structured sparsity assumptions on the spectrum of  $\Theta^*$* , etc. can also be handled under the paradigm of this paper.

## 2.2 Structured Matrix Estimator

Let  $\mathcal{R}$  be the norm surrogate for the structural constraints on  $\Theta^*$ , and  $\mathcal{R}^*$  denote its dual norm. We propose and analyze two convex estimators for the task of structured matrix completion:

### Constrained Norm Minimizer

$$\hat{\Theta}_{\text{cn}} = \underset{\|\Theta\|_\infty \leq \frac{\alpha^*}{\sqrt{d_1 d_2}}}{\operatorname{argmin}} \mathcal{R}(\Theta) \quad \text{s.t. } \|P_\Omega(\Theta) - y\|_2 \leq \lambda_{\text{cn}}. \quad (9)$$

### Generalized Matrix Dantzig Selector

$$\hat{\Theta}_{\text{ds}} = \underset{\|\Theta\|_\infty \leq \frac{\alpha^*}{\sqrt{d_1 d_2}}}{\operatorname{argmin}} \mathcal{R}(\Theta) \quad \text{s.t. } \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathcal{R}^* P_\Omega^*(P_\Omega(\Theta) - y) \leq \lambda_{\text{ds}}, \quad (10)$$

where  $P_\Omega^* : \mathbb{R}^\Omega \rightarrow \mathbb{R}^{d_1 \times d_2}$  is the linear adjoint of  $P_\Omega$ , i.e.  $\langle P_\Omega(X), y \rangle = \langle X, P_\Omega^*(y) \rangle$ .

**Note:** Theorem 1a–1b gives consistency results for (9) and (10), respectively, under certain conditions on the parameters  $\lambda_{\text{cn}} > 0$ ,  $\lambda_{\text{ds}} > 0$ , and  $\alpha^* > 1$ . In particular, these conditions assume knowledge of the noise variance  $\xi^2$  and spikiness ratio  $\alpha_{\text{sp}}(\Theta^*)$ . In practice, typically  $\xi$  and  $\alpha_{\text{sp}}(\Theta^*)$  are unknown and the parameters are tuned by validating on held out data.

## 3. Main Results

We define the following “restricted” *error cone* and its subset:

$$\mathcal{T}_{\mathcal{R}} = \mathcal{T}_{\mathcal{R}}(\Theta^*) = \operatorname{cone}\{\Delta : \mathcal{R}(\Theta^* + \Delta) \leq \mathcal{R}(\Theta^*)\}, \text{ and } \mathcal{E}_{\mathcal{R}} = \mathcal{T}_{\mathcal{R}} \cap \mathbb{S}^{d_1 d_2 - 1}. \quad (11)$$

Let  $\hat{\Theta}_{\text{cn}}$  and  $\hat{\Theta}_{\text{ds}}$  be the estimates from (9) and (10), respectively. If  $\lambda_{\text{cn}}$  and  $\lambda_{\text{ds}}$  are chosen such that  $\Theta^*$  belongs to the feasible sets in (9) and (10), respectively, then the error matrices  $\hat{\Delta}_{\text{cn}} = \hat{\Theta}_{\text{cn}} - \Theta^*$  and  $\hat{\Delta}_{\text{ds}} = \hat{\Theta}_{\text{ds}} - \Theta^*$  are contained in  $\mathcal{T}_{\mathcal{R}}$ .

**Theorem 1a** (Constrained Norm Minimizer). *Under the problem setup in Section 2, let  $\hat{\Theta}_{\text{cn}} = \Theta^* + \hat{\Delta}_{\text{cn}}$  be the estimate from (9) with  $\lambda_{\text{cn}} = 2\xi\sqrt{|\Omega|}$ . For large enough  $c_0$ , if  $|\Omega| > c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d$ , then there exists an RSC parameter  $\kappa_{c_0} > 0$  with  $\kappa_{c_0} \approx 1 - o\left(\frac{1}{\sqrt{\log d}}\right)$ , and constants  $c_1$  and  $c_2$  such that, with probability greater than  $1 - \exp(-c_1 w_G^2(\mathcal{E}_{\mathcal{R}})) - 2 \exp(-c_2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d)$ ,*

$$\frac{1}{d_1 d_2} \|\hat{\Delta}_{\text{cn}}\|_F^2 \leq 4 \max \left\{ \frac{\xi^2}{\kappa_{c_0}}, \frac{\alpha^{*2}}{d_1 d_2} \sqrt{\frac{c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d}{|\Omega|}} \right\}.$$

**Theorem 1b** (Matrix Dantzig Selector). *Under the problem setup in Section 2, let  $\hat{\Theta}_{\text{ds}} = \Theta^* + \hat{\Delta}_{\text{ds}}$  be the estimate from (10) with  $\lambda_{\text{ds}} \geq 2\xi \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathcal{R}^* P_\Omega^*(\eta)$ . For large enough  $c_0$ , if  $|\Omega| > c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d$ ,*

then there exists an RSC parameter  $\kappa_{c_0} > 0$  with  $\kappa_{c_0} \approx 1 - o\left(\frac{1}{\sqrt{\log d}}\right)$ , and a constant  $c_1$  such that, with probability greater than  $1 - \exp(-c_1 w_G^2(\mathcal{E}_\mathcal{R}))$ ,

$$\frac{1}{d_1 d_2} \|\hat{\Delta}_{ds}\|_F^2 \leq 16 \max \left\{ \frac{\lambda_{ds}^2 \Psi_{\mathcal{R}}^2(\mathcal{T}_{\mathcal{R}})}{\kappa_{c_0}^2}, \frac{\alpha^{*2}}{d_1 d_2} \sqrt{\frac{c_0^2 w_G^2(\mathcal{E}_\mathcal{R}) \log d}{|\Omega|}} \right\}.$$

Recall Gaussian width  $w_G$  and subspace compatibility constant  $\Psi_{\mathcal{R}}$  from (1) and (4), respectively. **Remarks:**

1. If  $\mathcal{R}(\Theta) = \|\Theta\|_*$  and  $\text{rank}(\Theta^*) = r$ , then  $w_G^2(\mathcal{E}_\mathcal{R}) \leq 3dr$ ,  $\Psi_{\mathcal{R}}(\mathcal{T}_{\mathcal{R}}) \leq 8\sqrt{r}$  and  $\frac{\sqrt{d_1 d_2}}{|\Omega|} \|P_{\Omega}^*(\eta)\|_2 \leq 2\sqrt{\frac{d \log d}{|\Omega|}}$  w.h.p Chandrasekaran et al. (2012); Fazel et al. (2001); Negahban and Wainwright (2012). Using these bounds in Theorem 1b recovers near-optimal results for low rank matrix completion under spikiness assumption Negahban and Wainwright (2012).
2. For both estimators, upper bound on sample complexity is dominated by the square of Gaussian width which is often considered the *effective dimension* of a subset in high dimensional space and plays a key role in high dimensional estimation under Gaussian measurement ensembles. The results show that, independent of  $\mathcal{R}(\cdot)$ , the upper bound on sample complexity for consistent matrix completion with highly localized measurements is within a  $\log d$  factor of the known sample complexity of  $\sim w_G^2(\mathcal{E}_\mathcal{R})$  for estimation from Gaussian measurements (Banerjee et al., 2014; Chandrasekaran et al., 2012; Vershynin, 2014; Cai et al., 2014).
3. First term in estimation error bounds in Theorem 1a–1b scales with  $\xi^2$  which is the per observation noise variance (upto constant). The second term is an upper bound on error that arises due to unidentifiability of  $\Theta^*$  within a certain radius under the spikiness constraints (Negahban and Wainwright, 2012); in contrast Candés and Plan (2010) show exact recovery when  $\xi = 0$  using more stringent matrix incoherence conditions.
4. Bound on  $\hat{\Delta}_{cn}$  from Theorem 1a is comparable to the result by Candés et al. Candés and Plan (2010) for low rank matrix completion under non-low-noise regime, where the first term dominates, and those of Chandrasekaran et al. (2012); Tropp (2014) for high dimensional estimation under Gaussian measurements. With a bound on  $w_G^2(\mathcal{E}_\mathcal{R})$ , it is easy to specialize this result for new structural constraints. However, this bound is potentially loose and asymptotically converges to a constant error proportional to the noise variance  $\xi^2$ .
5. The estimation error bound in Theorem 1b is typically sharper than that in Theorem 1a. However, for specific structures, using application of Theorem 1b requires additional bounds on  $\mathcal{R}^* P_{\Omega}^*(\eta)$  and  $\Psi_{\mathcal{R}}(\mathcal{T}_{\mathcal{R}})$  besides  $w_G^2(\mathcal{E}_\mathcal{R})$ .

### 3.1 Partial Complexity Measures

Recall that for  $w_G(S) = \mathbb{E} \sup_{X \in S} \langle X, G \rangle$  and  $\mathbb{R}^{|\Omega|} \ni g \sim \mathcal{N}(0, I_{|\Omega|})$  is a standard normal vector.

**Definition 6** (Partial Complexity Measures). *Given a randomly sampled  $\Omega = \{E_k \in \mathbb{R}^{d_1 \times d_2}\}$ , and a centered random vector  $\eta \in \mathbb{R}^{|\Omega|}$ , the partial  $\eta$ -complexity measure of  $S$  is given by:*

$$w_{\Omega, \eta}(S) = \mathbb{E}_{\Omega, \eta} \sup_{X \in S} \langle X, P_{\Omega}^*(\eta) \rangle. \quad (12)$$

Special cases of  $\eta$  being a vector of standard Gaussian  $g$ , or standard Rademacher  $\epsilon$  (i.e.  $\epsilon_k \in \{-1, 1\}$  w.p. 1/2) variables, are of particular interest.

**Note:** In the case of symmetric  $\eta$ , like  $g$  and  $\epsilon$ ,  $w_{\Omega, \eta}(S) = 2\mathbb{E}_{\Omega, \eta} \sup_{X \in S} \langle X, P_{\Omega}^*(\eta) \rangle$ , and the later expression will be used interchangeably ignoring the constant term.  $\square$

**Theorem 2** (Partial Gaussian Complexity). *Let  $S \subseteq \mathbb{B}^{d_1 d_2}$  with non-empty interior, and let  $\Omega$  be sampled according to (6).  $\exists$  universal constants  $k_1, k_2, K_1$  and  $K_2$  such that:*

$$\begin{aligned} w_{\Omega, g}(S) &\leq k_1 \sqrt{\frac{|\Omega|}{d_1 d_2}} w_G(S) + k_2 \sqrt{\mathbb{E}_{\Omega} \sup_{X, Y \in S} \|P_{\Omega}(X - Y)\|_2^2} \\ w_{\Omega, g}(S) &\leq K_1 \sqrt{\frac{|\Omega|}{d_1 d_2}} w_G(S) + K_2 \sup_{X, Y \in S} \|X - Y\|_{\infty}. \end{aligned} \quad (13)$$

Also, for centered i.i.d. sub-Gaussian vector  $\eta \in \mathbb{R}^{|\Omega|}$ ,  $\exists$  constant  $K_3$  s.t.  $w_{\Omega, \eta}(S) \leq K_3 w_{\Omega, g}(S)$ .

**Note:** For  $\Omega \subsetneq [d_1] \times [d_2]$ , the second term in (13) is a consequence of the localized measurements.

### 3.2 Spectral $k$ -Support Norm

We introduced spectral  $k$ -support norm in Section 2.1. The estimators from (9) and (10) for spectral  $k$ -support norm can be efficiently solved via proximal methods using the proximal operators derived in McDonald et al. (2014). We are interested in the statistical guarantees for matrix completion using spectral  $k$ -support norm regularization. We extend the analysis for upper bounding the Gaussian width of the descent cone for the vector  $k$ -support norm by Richard et al. (2014) to the case of spectral  $k$ -support norm. WLOG let  $d_1 = d_2 = \bar{d}$ . Let  $\sigma^* \in \mathbb{R}^{\bar{d}}$  be the vector of singular values of  $\Theta^*$  sorted in non-ascending order. Let  $r \in \{0, 1, 2, \dots, k-1\}$  be the unique integer satisfying:  $\sigma_{k-r-1}^* > \frac{1}{r+1} \sum_{i=k-r}^p \sigma_i^* \geq \sigma_{k-r}^*$ . Denote  $I_2 = \{1, 2, \dots, k-r-1\}$  and  $I_1 = \{k-r, k-r+1, \dots, s\}$ . Finally, for  $I \subseteq [\bar{d}]$ ,  $(\sigma_I^*)_i = 0 \ \forall i \in I^c$ , and  $(\sigma_I^*)_i = \sigma_i^* \ \forall i \in I$ .

**Lemma 3.** *If rank of  $\Theta^*$  is  $s$  and  $\mathcal{E}_{\mathcal{R}}$  is the error set for  $\mathcal{R}(\Theta) = \|\Theta\|_{k-sp}$ , then*

$$w_G^2(\mathcal{E}_{\mathcal{R}}) \leq s(2\bar{d} - s) + \left( \frac{(r+1)^2 \|\sigma_{I_2}^*\|_2^2}{\|\sigma_{I_1}^*\|_1^2} + |I_1| \right) (2\bar{d} - s).$$

Proof of the above lemma is provided in the appendix. Lemma 3 can be combined with Theorem 1a to obtain recovery guarantees for matrix completion under spectral  $k$ -support norm.

## 4. Discussions and Related Work

**Sample Complexity:** For consistent recovery in high dimensional convex estimation, it is desirable that the descent cone at the target parameter  $\Theta^*$  is “small” relative to the feasible set (enforced by the observations) of the estimator. Thus, it is not surprising that the sample complexity and estimation error bounds of an estimator depends on some measure of complexity/size of the error cone at  $\Theta^*$ . Results in this paper are largely characterized in terms of a widely used complexity measure of Gaussian width  $w_G(\cdot)$ , and can be compared with the literature on estimation from Gaussian measurements.

**Error Bounds:** Theorem 1a provides estimation error bounds that depends only on the Gaussian width of the descent cone. In non-low-noise regime, this result is comparable to analogous results of constrained norm minimization Candés et al. (2011); Chandrasekaran et al. (2012); Tropp (2014). However, this bound is potentially loose owing to mismatched data-fit term using squared loss, and asymptotically converges to a constant error proportional to the noise variance  $\xi^2$ .

A tighter analysis on the estimation error can be obtained for the matrix Dantzig selector (10) from



Theorem 1b. However, application of Theorem 1b requires computing high probability upper bound on  $\mathcal{R}^*P_\Omega^*(\eta)$ . The literature on norms of random matrices Edelman (1988); Litvak et al. (2005); Vershynin (2012); Tropp (2012) can be exploited in computing such bounds. Beside, in special cases: if  $\mathcal{R}(\cdot) \geq K\|\cdot\|_*$ , then  $K\mathcal{R}^*(\cdot) \leq \|\cdot\|_{\text{op}}$  can be used to obtain asymptotically consistent results.

Finally, under near zero-noise, the second term in the results of Theorem 1 dominates, and bounds are weaker than that of Candés et al. (2011); Keshavan et al. (2010b) owing to the relaxation of stronger incoherence assumption.

**Related Work and Future Directions:** The closest related work is the result on consistency of matrix completion under decomposable norm regularization by Gunasekar et al. (2014). Results in this paper are a strict generalization to general norm regularized (not necessarily decomposable) matrix completion. We provide non-trivial examples of application where structures enforced by such non-decomposable norms are of interest. Further, in contrast to our results that are based on Gaussian width, the RSC parameter in Gunasekar et al. (2014) depends on a modified complexity measure  $\kappa_{\mathcal{R}}(d, |\Omega|)$  (see definition in Gunasekar et al. (2014)). An advantage of results based on Gaussian width is that, application of Theorem 1 for special cases can greatly benefit from the numerous tools in the literature for the computation of  $w_G(\cdot)$ .

Another closely related line of work is the non-asymptotic analysis of high dimensional estimation under random Gaussian or sub-Gaussian measurements Chandrasekaran et al. (2012); Amelunxen et al. (2014); Tropp (2014); Banerjee et al. (2014); Vershynin (2014); Cai et al. (2014). However, the analysis from this literature rely on variants of RIP of the measurement ensemble Candés and Tao (2005), which is not satisfied by the the extremely localized measurements encountered in matrix completion Candés and Recht (2009). In an intermediate result, we establish a form of RSC for matrix completion under general norm regularization: a result that was previously known only for nuclear norm and decomposable norm regularization.

In future work, it is of interest to derive matching lower bounds on estimation error for matrix completion under general low dimensional structures, along the lines of Koltchinskii et al. (2011); Cai et al. (2014) and explore special case applications of the results in the paper. We also plan to derive explicit characterization of  $\lambda_{\text{ds}}$  in terms of Gaussian width of unit balls by exploiting generic chaining results for general Banach spaces Talagrand (2014).

## 5. Proof Sketch

Proofs of the lemmas are provided in the Appendix.

### 5.1 Proof of Theorem 1

Define the following set of  $\beta$ -non-spiky matrices in  $\mathbb{R}^{d_1 \times d_2}$  for constant  $c_0$  from Theorem 1:

$$\mathbb{A}(\beta) = \left\{ X : \alpha_{\text{sp}}(X) = \frac{\sqrt{d_1 d_2} \|X\|_\infty}{\|X\|_F} < \beta \right\}. \quad (14)$$

Define,

$$\beta_{c_0}^2 = \sqrt{\frac{|\Omega|}{c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d}} \quad (15)$$

**Case 1: Spiky Error Matrix** When the error matrix from (9) or (10) has large spikiness ratio, following bound on error is immediate using  $\|\hat{\Delta}\|_\infty \leq \|\hat{\Theta}\|_\infty + \|\Theta^*\|_\infty \leq 2\alpha^*/\sqrt{d_1 d_2}$  in (3).

**Proposition 4** (Spiky Error Matrix). *For the constant  $c_0$  in Theorem 1a, if  $\alpha_{sp}(\hat{\Delta}_{cn}) \notin \mathbb{A}(\beta_{c_0})$ , then  $\|\hat{\Delta}_{cn}\|_F^2 \leq \frac{4\alpha^{*2}}{\beta_{c_0}^2} = 4\alpha^{*2} \sqrt{\frac{c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d}{|\Omega|}}$ . An analogous result also holds for  $\hat{\Delta}_{ds}$ .*  $\square$

**Case 2: Non-Spiky Error Matrix** Let  $\hat{\Delta}_{ds}, \hat{\Delta}_{cn} \in \mathbb{A}(\beta)$ . Recall from (5), that  $y - P_{\Omega}(\Theta^*) = \xi\eta$ , where  $\eta \in \mathbb{R}^{|\Omega|}$  consists of independent sub-Gaussian random variables with  $\mathbb{E}[\eta_k] = 0$ ,  $\text{Var}(\eta_k) = 1$ , and  $\|\eta_k\|_{\Psi_2} \leq b$  for a constant  $b$ .

### 5.1.1 RESTRICTED STRONG CONVEXITY (RSC)

Recall  $\mathcal{T}_{\mathcal{R}}$  and  $\mathcal{E}_{\mathcal{R}}$  from (11). The most significant step in the proof of Theorem 1 involves showing that over a useful subset of  $\mathcal{T}_{\mathcal{R}}$ , a form of RSC (2) is satisfied by a squared loss penalty.

**Theorem 5** (Restricted Strong Convexity). *Let  $|\Omega| > c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d$ , for large enough constant  $c_0$ . There exists a RSC parameter  $\kappa_{c_0} > 0$  with  $\kappa_{c_0} \approx 1 - o\left(\frac{1}{\sqrt{\log d}}\right)$ , and a constant  $c_1$  such that, the following holds w.p. greater than  $1 - \exp(-c_1 w_G^2(\mathcal{E}_{\mathcal{R}}))$ ,*

$$\forall X \in \mathcal{T}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0}), \quad \frac{d_1 d_2}{|\Omega|} \|P_{\Omega}(X)\|_2^2 \geq \kappa_{c_0} \|X\|_F^2.$$

Proof in Appendix A combines empirical process tools along with Theorem 2.  $\square$

### 5.1.2 CONSTRAINED NORM MINIMIZER

**Lemma 6.** *Under the conditions of Theorem 1, let  $b$  be a constant such that  $\forall k, \|\eta_k\|_{\Psi_2} \leq b$ . There exists a universal constant  $c_2$  such that, if  $\lambda_{cn} \geq 2\xi \sqrt{|\Omega|}$ , then w.p. greater than  $1 - 2 \exp(-c_2 |\Omega|)$ , (a)  $\hat{\Delta}_{ds} \in \mathcal{T}_{\mathcal{R}}$ , and (b)  $\|P_{\Omega}(\hat{\Delta}_{cn})\|_2 \leq 2\lambda_{cn}$ .*  $\square$

Using  $\lambda_{cn} = 2\xi \sqrt{|\Omega|}$  in (9), if  $\hat{\Delta}_{cn} \in \mathbb{A}(\beta_{c_0})$ , then using Theorem 5 and Lemma 6, w.h.p.

$$\frac{\|\hat{\Delta}_{cn}\|_F^2}{d_1 d_2} \leq \frac{1}{\kappa_{c_0}} \frac{\|P_{\Omega}(\hat{\Delta}_{cn})\|_2^2}{|\Omega|} \leq \frac{4\xi^2}{\kappa_{c_0}}. \quad (16)$$

### 5.1.3 MATRIX DANTZIG SELECTOR

**Proposition 7.**  $\lambda_{ds} \geq \xi \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathcal{R}^* P_{\Omega}^*(\eta) \Rightarrow \text{w.h.p. (a) } \hat{\Delta}_{ds} \in \mathcal{T}_{\mathcal{R}}; \text{ (b) } \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathcal{R}^* P_{\Omega}^*(P_{\Omega}(\hat{\Delta}_{ds})) \leq 2\lambda_{ds}.$

Above result follows from optimality of  $\hat{\Theta}_{ds}$  and triangle inequality. Also,

$$\frac{\sqrt{d_1 d_2}}{|\Omega|} \|P_{\Omega}(\hat{\Delta}_{ds})\|_2^2 \leq \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathcal{R}^* P_{\Omega}^*(P_{\Omega}(\hat{\Delta}_{ds})) \mathcal{R}(\hat{\Delta}_{ds}) \leq 2\lambda_{ds} \Psi_{\mathcal{R}}(\mathcal{T}_{\mathcal{R}}) \|\hat{\Delta}_{ds}\|_F,$$

where recall norm compatibility constant  $\Psi_{\mathcal{R}}(\mathcal{T}_{\mathcal{R}})$  from (4). Finally, using Theorem 5, w.h.p.

$$\frac{\|\hat{\Delta}_{ds}\|_F^2}{d_1 d_2} \leq \frac{1}{|\Omega|} \frac{\|P_{\Omega}(\hat{\Delta}_{ds})\|_2^2}{\kappa_{c_0}} \leq \frac{4\lambda_{ds} \Psi_{\mathcal{R}}(\mathcal{T}_{\mathcal{R}})}{\kappa_{c_0}} \frac{\|\hat{\Delta}_{ds}\|_F}{\sqrt{d_1 d_2}}. \quad (17)$$

## 5.2 Proof of Theorem 2

Let the entries of  $\Omega = \{E_k = e_{i_k} e_{j_k}^\top : k = 1, 2, \dots, |\Omega|\}$  be sampled as in (6). Recall that  $g \in \mathbb{R}^{|\Omega|}$  is a standard normal vector. For a compact  $S \subseteq \mathbb{R}^{d_1 \times d_2}$ , it suffices to prove Theorem 2 for a dense countable subset of  $S$ . Overloading  $S$  to such a countable subset, define following random process:

$$(\mathcal{X}_{\Omega,g}(X))_{X \in S}, \text{ where } \mathcal{X}_{\Omega,g}(X) = \langle X, P_\Omega^*(g) \rangle = \sum_k \langle X, E_k \rangle g_k. \quad (18)$$

We start with a key lemma in the proof of Theorem 2. Proof of this lemma, provided in Appendix B, uses tools from the broad topic of generic chaining developed in recent works Talagrand (1996, 2014).

**Lemma 8.** *For a compact subset  $S \subseteq \mathbb{R}^{d_1 \times d_2}$  with non-empty interior,  $\exists$  constants  $k_1, k_2$  such that:*

$$w_{\Omega,g}(S) = \mathbb{E} \sup_{X \in S} \mathcal{X}_{\Omega,g}(X) \leq k_1 \sqrt{\frac{|\Omega|}{d_1 d_2}} w_G(S) + k_2 \sqrt{\mathbb{E} \sup_{X,Y \in S} \|P_\Omega(X - Y)\|_2^2}. \quad \square$$

**Lemma 9.** *There exists constants  $k_3, k_4$ , such that for compact  $S \subseteq \mathbb{B}^{d_1 d_2}$  with non-empty interior*

$$\mathbb{E} \sup_{X,Y \in S} \|P_\Omega(X - Y)\|_2^2 \leq k_3 \frac{|\Omega|}{d_1 d_2} w_G^2(S) + k_4 \left( \sup_{X,Y \in S} \|X - Y\|_\infty \right) w_{\Omega,g}(S)$$

Theorem 2 follows by combining Lemma 8 and Lemma 9, and simple algebraic manipulations using  $\sqrt{ab} \leq a/2 + b/2$  and triangle inequality (See Appendix B.4).

The statement in Theorem 2 about partial sub-Gaussian complexity follows from a standard result in empirical process given in Lemma 11 in the appendix.  $\square$

**Acknowledgments** We thank the anonymous reviewers for helpful comments and suggestions. S. Gunasekar and J. Ghosh acknowledge funding from NSF grants IIS-1421729, IIS-1417697, and IIS1116656. A. Banerjee acknowledges NSF grants IIS-1447566, IIS-1422557, CCF-1451986, CNS-1314560, IIS-0953274, IIS-1029711, and NASA grant NNX12AQ39A.

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## Supplementary Material: Unified View of Matrix Completion under General Structural Constraints

Suriya Gunasekar, Arindam Banerjee, Joydeep Ghosh

Note: Background and preliminaries are provided in Appendix D.

### Appendix A. Appendix to Proof of Theorem 1

#### A.1 Proof of Theorem 5

##### Statement of Theorem 5:

Let  $|\Omega| > c_0^2 w_G^2(\mathcal{E}_{\mathcal{R}}) \log d$ , for large enough constant  $c_0$ . There exists a RSC parameter  $\kappa_{c_0} > 0$  with  $\kappa_{c_0} \approx 1 - o\left(\frac{1}{\sqrt{\log d}}\right)$ , and a constant  $c_1$  such that, the following holds w.p. greater than  $1 - \exp(-c_1 w_G^2(\mathcal{E}_{\mathcal{R}}))$ ,

$$\forall X \in \mathcal{T}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0}), \quad \frac{d_1 d_2}{|\Omega|} \|P_{\Omega}(X)\|_2^2 \geq \kappa_{c_0} \|X\|_F^2.$$

**Proof:** Recall that  $\mathcal{T}_{\mathcal{R}} = \{\Delta : \mathcal{R}(\Theta^* + \Delta) \leq \mathcal{R}(\Theta^*)\}$  and  $\mathcal{E}_{\mathcal{R}} = \mathcal{T}_{\mathcal{R}} \cap \mathbb{S}^{d_1 d_2 - 1}$ . Using the properties of norms, it can be easily verified that for the non-trivial case of  $\Theta^* \neq 0$ ,  $\mathcal{T}_{\mathcal{R}}$  is a cone with non-empty interior.

We use Theorem 2 as a key result in this proof.

Define  $\bar{\mathcal{E}}_{\mathcal{R}} = \mathcal{T}_{\mathcal{R}} \cap \mathbb{B}^{d_1 d_2}$ .

$\bar{\mathcal{E}}_{\mathcal{R}}$  is a compact subset of  $\mathcal{T}_{\mathcal{R}}$  with non-empty interior, which satisfies the conditions of Theorem 2.

Also, since  $\mathcal{T}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})$  is a cone, the following can be easily verified:

$$\begin{aligned} w_{\Omega, g}(\bar{\mathcal{E}}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})) &= w_{\Omega, g}(\mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})) \\ w_G(\bar{\mathcal{E}}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})) &= w_G(\mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})) \leq w_G(\mathcal{E}_{\mathcal{R}}) \end{aligned} \tag{19}$$

We define a random variable  $V(\Omega) = \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left| \frac{d_1 d_2}{|\Omega|} \|P_{\Omega}(X)\|_2^2 - 1 \right|$ .

Note that:  $\mathbb{E} \frac{d_1 d_2}{|\Omega|} \|P_{\Omega}(X)\|_2^2 = 1$ ; and

for  $X \in \mathbb{A}(\beta_{c_0})$ ,  $\|X\|_{\infty} \leq \frac{\beta_{c_0}}{\sqrt{d_1 d_2}}$ .

##### A.1.1 EXPECTATION OF $V(\Omega)$

Recall that  $\Omega = \{E_k : s = 1, 2, \dots, |\Omega|\}$  are sampled uniformly from standard basis for  $\mathbb{R}^{d_1 \times d_2}$ ,  $(\epsilon_k)$  are a sequence of independent Rademacher variables, and  $w_G(\cdot)$  denotes the Gaussian width. For constant  $k_1, k_2, k_3$  not necessarily same in each occurrence:

$$\begin{aligned} \mathbb{E} V(\Omega) &\stackrel{(a)}{\leq} \frac{2d_1 d_2}{|\Omega|} \mathbb{E} \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left| \sum_{k=1}^{|\Omega|} \langle X, E_k \rangle^2 \epsilon_k \right| \stackrel{(b)}{\leq} k_1 \beta_{c_0} \frac{\sqrt{d_1 d_2}}{|\Omega|} \mathbb{E} \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left| \sum_{k=1}^{|\Omega|} \langle X, E_k \rangle \epsilon_k \right| \\ &= k_1 \beta_{c_0} \frac{\sqrt{d_1 d_2}}{|\Omega|} w_{\Omega, \epsilon}(\bar{\mathcal{E}}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})) \stackrel{(c)}{\leq} k_1 \sqrt{\frac{\beta_{c_0}^2 w_G^2(\mathcal{E}_{\mathcal{R}})}{|\Omega|}} + k_2 \frac{\beta_{c_0}^2}{|\Omega|} \leq \frac{k_3}{c_0 \sqrt{\log d}}, \end{aligned} \tag{20}$$

where (a) follows from symmetrization (Lemma 18), (b) from contraction principle as  $\phi_k(\langle X, E_k \rangle) = \frac{\langle X, E_k \rangle^2}{2 \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \|X\|_{\infty}}$  is a contraction (Lemma 19), and (c) follows from Theorem 2.

### A.1.2 CONCENTRATION ABOUT $\mathbb{E}V(\Omega)$

Let  $\Omega' \subset [m] \times [n]$  be another set of indices that differ from  $\Omega$  in exactly one element. We have:

$$\begin{aligned} V(\Omega) - V(\Omega') &= \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left| \frac{d_1 d_2}{|\Omega|} \sum_{ij \in \Omega} X_{ij}^2 - 1 \right| - \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left| \frac{d_1 d_2}{|\Omega|} \sum_{kl \in \Omega'} X_{kl}^2 - 1 \right| \\ &\leq \frac{d_1 d_2}{|\Omega|} \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \left( \left| \sum_{ij \in \Omega} X_{ij}^2 - \sum_{kl \in \Omega'} X_{kl}^2 \right| \right) \\ &\leq \frac{2d_1 d_2}{|\Omega|} \sup_{X \in \mathcal{E}_{\mathcal{R}} \cap \mathbb{A}(\beta_{c_0})} \|X\|_{\infty}^2 \leq \frac{2\beta_{c_0}^2}{|\Omega|}. \end{aligned} \quad (21)$$

By similar arguments on  $V(\Omega') - V(\Omega)$ ,  $|V(\Omega) - V(\Omega')| \leq \frac{2\beta_{c_0}^2}{|\Omega|}$ . Therefore, using Mc Diarmid's inequality (34), we have  $P(V(\Omega) > \mathbb{E}V(\Omega) + \delta) \leq \exp\left(-c'_1 \frac{\delta^2 |\Omega|}{\beta_{c_0}^4}\right)$ . Using  $\delta = \frac{1}{c_0 \sqrt{\log d}}$ , we have

$$P\left(V(\Omega) > \frac{k'_3}{c_0 \sqrt{\log d}}\right) \leq \exp\left(-c_1 w_G^2(\mathcal{E}_{\mathcal{R}})\right),$$

where  $c_0$  is a constant that can be chosen independent of  $k_3$ . Choosing  $c_0$  large enough, we can set  $\kappa_{c_0} := 1 - \delta_{c_0} = 1 - \frac{k'_3}{c_0 \sqrt{\log d}}$  close to 1.  $\square$

## A.2 Proof of Lemma 6

Recall that  $\eta \in \mathbb{R}^{|\Omega|}$  is a vector of centered, unit variance sub-Gaussian random variables with  $\|\eta_k\|_{\Psi_2} \leq b$ . Combining Lemma 25 and Lemma 26, we have that  $\eta_k^2$  and  $\eta_k^2 - 1$  are sub-exponential with  $\|\eta_k^2 - 1\|_{\Psi_1} \leq 2\|\eta_k^2\|_{\Psi_1} \leq 4\|\eta_k\|_{\Psi_2} \leq 4b^2$ . Thus, using Lemma 24, for a constant  $c'_2$ , we have:

$$\mathbb{P}\left(\left|\frac{1}{|\Omega|} \sum_{k=1}^{|\Omega|} \eta_k^2 - 1\right| > \tau\right) \leq 2 \exp\left(-c'_2 |\Omega| \min\left\{\frac{\tau^2}{16b^4}, \frac{\tau}{4b^2}\right\}\right). \quad (22)$$

Choosing  $\tau$  to be an appropriate constant, we have  $\|P_{\Omega}(\Theta^*) - y\|_2 \leq 2\xi \sqrt{|\Omega|} \leq \lambda_{\text{cn}}$  w.p. greater than  $1 - \exp(-c_2 \tau |\Omega|)$ , and the lemma follows from the optimality of  $\hat{\Theta}_{\text{cn}}$  and triangle inequality.

## Appendix B. Appendix to Proof of Theorem 2

### B.1 Results from Generic Chaining

In this section,  $K$  denotes a universal constant, not necessarily the same at each occurrence.

**Definition 7** (Gamma Functional (Definition 2.2.19 in Talagrand (2014))). Given a complete pseudometric space  $(T, d)$ , an *admissible sequence* is an increasing sequence  $(\mathcal{A}_n)$  of partitions of  $T$  such that  $|\mathcal{A}_0| = 1$  and  $|\mathcal{A}_n| \leq 2^{2^n}$  for  $n \geq 1$ . For  $\alpha > 0$ , we define the Gamma functional  $\gamma_{\alpha}(T, d)$  as follows:

$$\gamma_{\alpha}(T, d) = \inf_{(\mathcal{A}_n)_{n \geq 0}} \sup_{t \in T} \sum_{n \geq 0} 2^{n/\alpha} \Delta_d(A_n(t)), \quad (23)$$

where  $\inf$  is over all admissible sequences  $(\mathcal{A}_n)$ ,  $A_n(t)$  is the unique element of  $\mathcal{A}_n$  that contains  $t$ , and  $\Delta_d(A)$  is the diameter of the set  $A$  measured in metric  $d$ .

**Lemma 10** (Majorizing Measures Theorem (Theorem 2.4.1 in Talagrand (2014))). *Given a closed set  $T$  in a metric space, let  $(X_t)_{t \in T}$  be a centered Gaussian process indexed by  $t \in T$ , i.e.  $(X_t)$  are jointly Gaussian. For  $s, t \in T$ , let  $d_X(s, t) := \sqrt{\mathbb{E}(X_s - X_t)^2}$  denote the canonical pseudometric associated with  $(X_t)$ . We then have :*

$$\frac{1}{K} \gamma_2(T, d_X) \leq \mathbb{E} \sup_{t \in T} X_t \leq K \gamma_2(T, d_X).$$

*In particular, considering the canonical Gaussian process  $(\sum_i t_i g_i)_{t \in T}$ , we have:*

$$\frac{1}{K} \gamma_2(T, \|\cdot\|_F) \leq w_G(T) \leq K \gamma_2(T, \|\cdot\|_F).$$

**Lemma 11** (Theorem 2.4.12 in Talagrand (2014)). *Let  $(X_t)_{t \in T}$  be a centered Gaussian process with canonical distance  $d_X = \sqrt{\mathbb{E}(X_s - X_t)^2}$ . Let  $(Y_t)_{t \in T}$  be another centered process indexed by the same set  $T$ , such that it satisfies the following condition:*

$$\forall s, t \in T, u > 0, \quad \mathbb{P}(|Y_s - Y_t| > u) \leq 2 \exp\left(-\frac{u^2}{2d_X^2(s, t)}\right),$$

*then, we have  $\mathbb{E} \sup_{s, t \in T} |Y_s - Y_t| \leq K \mathbb{E} \sup_{t \in T} X_t$ .*

*If further,  $(Y_t)_{t \in T}$  is symmetric, then  $\mathbb{E} \sup_t |Y_t| \leq \mathbb{E} \sup_{s, t \in T} |Y_s - Y_t| = 2 \mathbb{E} \sup_{t \in T} Y_t$ .*

*Note that from the properties of sub-Gaussian random variables, the above lemma can be directly bound canonical sub-Gaussian complexity measures using canonical Gaussian complexities.*

**Lemma 12** (Theorem 3.1.4 in Talagrand (2014)). *Let  $T$  be a compact group with non-empty interior. Consider a translation invariant random distance  $d_\omega$ , that depends on a random parameter  $\omega$  and let  $d(s, t) = \sqrt{\mathbb{E} d_\omega^2(s, t)}$ , then :*

$$\left(\mathbb{E} \gamma_2^2(T, d_\omega)\right)^{1/2} \leq K \gamma_2(T, d) + K \left(\mathbb{E} \sup_{s, t \in T} d_\omega^2(s, t)\right)^{1/2}$$

## B.2 Proof of Lemma 8

### Statement of Lemma 8

For a compact subset  $S \subseteq \mathbb{R}^{d_1 \times d_2}$  with non-empty interior,  $\exists$  constants  $k_1, k_2$  such that:

$$w_{\Omega, g}(S) = \mathbb{E} \sup_{X \in S} \mathcal{X}_{\Omega, g}(X) \leq k_1 \sqrt{\frac{|\Omega|}{d_1 d_2}} w_G(S) + k_2 \sqrt{\mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2}. \quad \square$$

**Proof:** Recall definition of  $(\mathcal{X}_{\Omega, g}(X))_{X \in S}$  from (18), such that  $\mathcal{X}_{\Omega, g}(X) = \sum_k \langle X, E_k \rangle g_k$ .

By Fubini's theorem  $\mathbb{E}_{\Omega, g} \sup_{X \in S} \mathcal{X}_{\Omega, g}(X) = \mathbb{E}_\Omega \mathbb{E}_g \sup_{X \in S} \mathcal{X}_{\Omega, g}(X)$ .

Also, we have the following results:

- For a fixed  $\Omega$ ,  $(\mathcal{X}_{\Omega, g}(X))$  is a Gaussian process with a translation invariant canonical distance given by  $d_\Omega(X, Y) = \|P_\Omega(X - Y)\|_2^2$ .
- $d(X, Y) := \sqrt{E_\Omega d_\Omega^2(X, Y)} = \sqrt{\frac{|\Omega|}{d_1 d_2}} \|X - Y\|_F$

Using Lemma 10 we have:  $\mathbb{E}_g \sup_{X \in S} \mathcal{X}_{\Omega, g}(X) \leq K \gamma_2(S, d_\Omega)$ , and the following holds:

$$\begin{aligned} w_{\Omega, g}(S) &= \mathbb{E}_\Omega \mathbb{E}_g \sup_{X \in S} \mathcal{X}_{\Omega, g}(X) \leq K \mathbb{E}_\Omega \gamma_2(S, d_\Omega) \stackrel{(a)}{\leq} \sqrt{\mathbb{E}_\Omega \gamma_2^2(S, d_\Omega)} \\ &\stackrel{(b)}{\leq} K \sqrt{\frac{|\Omega|}{d_1 d_2}} \gamma_2(S, \|\cdot\|_F) + K \sqrt{\mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2}, \end{aligned} \quad (24)$$



where (a) follows from Jensen's inequality, (b) from Lemma 12 and noting that by definition  $\forall M > 0$ ,  $\gamma_2(T, Md) = M\gamma_2(T, d)$ . Lemma 8 now follows from (24) and Lemma 10.  $\square$

### B.3 Proof of Lemma 9

#### Statement of Lemma 9

There exists constants  $k_3, k_4$ , such that for compact  $S \subseteq \mathbb{B}^{d_1 d_2}$  with non-empty interior

$$\mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2 \leq k_3 \frac{|\Omega|}{d_1 d_2} w_G^2(S) + k_4 \sup_{X, Y \in S} \|X - Y\|_\infty w_{\Omega, g}(S)$$

**Proof:** Using triangle inequality, we have:

$$\mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2 \leq \mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2 - \mathbb{E} \|P_\Omega(X - Y)\|_2^2 + \sup_{X, Y \in S} \mathbb{E} \|P_\Omega(X - Y)\|_2^2 \quad (25)$$

Further,

$$\sup_{X, Y \in S} \mathbb{E} \|P_\Omega(X - Y)\|_2^2 = \frac{|\Omega|}{d_1 d_2} \sup_{X, Y} \|X - Y\|_F^2 \leq \frac{|\Omega|}{d_1 d_2} \gamma_2^2(S, \|\cdot\|_F)^2, \quad (26)$$

where the last inequality follows from the definition of  $\gamma_\alpha$ .

Finally, we have the following set of equations:

$$\begin{aligned} \mathbb{E} \sup_{X, Y \in S} \left| \|P_\Omega(X - Y)\|_2^2 - \mathbb{E}[\|P_\Omega(X - Y)\|_2^2] \right| &= \mathbb{E} \sup_{X, Y \in S} \left| \sum_{k=1}^{|\Omega|} \langle X - Y, E_k \rangle^2 - \mathbb{E} \langle X - Y, E_k \rangle^2 \right| \\ &\stackrel{(a)}{\leq} 2\mathbb{E}_{\Omega, (\epsilon_s)} \sup_{X, Y \in S} \left| \sum_{k=1}^{|\Omega|} \langle X - Y, E_k \rangle^2 \epsilon_k \right| \stackrel{(b)}{\leq} k'_4 \sup_{X \in S} \|X - Y\|_\infty \mathbb{E}_{\Omega, g} \sup_{X, Y \in S} \left| \sum_{k=1}^{|\Omega|} \langle X - Y, E_k \rangle g_k \right| \\ &\stackrel{(c)}{\leq} 2k'_4 \sup_{X, Y \in S} \|X - Y\|_\infty \mathbb{E}_{\Omega, g} \sup_{X \in S} \left| \sum_{k=1}^{|\Omega|} \langle X, E_k \rangle g_k \right| \stackrel{(d)}{\leq} 4k'_4 \sup_{X, Y \in S} \|X - Y\|_\infty w_{\Omega, g}(S), \end{aligned} \quad (27)$$

where  $(\epsilon_k)$  are standard Rademacher variables, i.e.  $\epsilon_k \in \{-1, 1\}$  with equal probability, (a) follows from symmetrization argument (Lemma 18), (b) follows from contraction principles Lemma 19 and using  $\phi(\langle X, E_k \rangle) = \frac{\langle X, E_k \rangle^2}{2 \sup_{X \in S} \|X\|_\infty}$  as a contraction, (c) follows from triangle inequality, and (d) follows from  $g_k$  being symmetric (Lemma 2.2.1 in Talagrand (2014)).  $\square$

The lemma follows by combining Lemma 10 and equations (25), (26), and (27).

### B.4 Remaining Steps in the Proof of Theorem 2

From Lemma 9, we have the following:

$$\begin{aligned} \sqrt{\mathbb{E} \sup_{X, Y \in S} \|P_\Omega(X - Y)\|_2^2} &\stackrel{(a)}{\leq} K_3 \sqrt{\frac{|\Omega|}{d_1 d_2} w_G(S)} + \sqrt{k_4 \left( \sup_{X, Y \in S} \|X - Y\|_\infty \right) w_{\Omega, g}(S)} \\ &\stackrel{(b)}{\leq} K_3 \sqrt{\frac{|\Omega|}{d_1 d_2} w_G(S)} + K_4 \left( \sup_{X, Y \in S} \|X - Y\|_\infty \right) + \frac{1}{2} w_{\Omega, g}(S), \end{aligned} \quad (28)$$

where (a) follows from triangle inequality, (b) using  $\sqrt{ab} \leq a/2 + b/2$ .

Bound on  $w_{\Omega, g}(S)$  in Theorem 2 follows by using (28) in Lemma 8.

## Appendix C. Spectral k-Support Norm

Recall the following definition of spectral  $k$ -support norm  $\|\Theta\|_{k\text{-sp}}$  from (8):

$$\|\Theta\|_{k\text{-sp}} = \inf_{v \in \mathcal{V}(\mathcal{G}_k)} \left\{ \sum_{g \in \mathcal{G}_k} \|v_g\|_2 : \sum_{g \in \mathcal{G}_k} v_g = \sigma(\Theta) \right\}, \quad (29)$$

where  $\mathcal{G}_k = \{g \subseteq [\bar{d}] : |g| \leq k\}$  is the set of all subsets  $[d]$  of cardinality at most  $k$ , and  $\mathcal{V}(\mathcal{G}_k) = \{(v_g)_{g \in \mathcal{G}_k} : v_g \in \mathbb{R}^{d_1}, \text{supp}(v_g) \subseteq g\}$ .

**Proposition 13** (Proposition 2.1 in Argyriou et al. (2012)). *For  $\Theta \in \mathbb{R}^{\bar{d} \times \bar{d}}$  with singular values  $\sigma(\Theta) = \{\sigma_1, \sigma_2, \dots, \sigma_{\bar{d}}\}$ , such that  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_{\bar{d}}$ . Then,*

$$\|\Theta\|_{k\text{-sp}} = \left( \sum_{i=1}^{k-r-1} \sigma_i^2 + \frac{1}{r+1} \left( \sum_{i=k-r}^{\bar{d}} \sigma_i \right)^2 \right)^{\frac{1}{2}}, \quad (30)$$

where  $r \in \{0, 1, 2, \dots, k-1\}$  is the unique integer satisfying  $\sigma_{k-r-1} > \frac{1}{r+1} \sum_{i=k-r}^{d_1} \sigma_i \geq \sigma_{k-r}$ .  $\square$

### C.1 Proof of Lemma 3

#### Statement of Lemma 3

If rank of  $\Theta^*$  is  $s$  and  $\mathcal{E}_{\mathcal{R}}$  is the error set from  $\mathcal{R}(\Theta) = \|\Theta\|_{k\text{-sp}}$ , then

$$w_G^2(\mathcal{E}_{\mathcal{R}}) \leq s(2\bar{d} - s) + \left( \frac{(r+1)^2 \|\sigma_{I_2}^*\|_2^2}{\|\sigma_{I_1}^*\|_1^2} + |I_1| \right) (2\bar{d} - s).$$

$\square$

**Proof** We state the following lemmas from existing work.

**Lemma 14** (Equation 60 in Richard et al. (2014)). *Let  $z$  be an  $s \geq k$  sparse vector in  $\mathbb{R}^p$ , and let  $\tilde{z}$  is the vector  $z$  sorted in non increasing order of  $|z_i|$ . Denote  $r \in \{0, 1, 2, \dots, k-1\}$  to be the unique integer satisfying*

$$|\tilde{z}_{k-r-1}| > \frac{1}{r+1} \sum_{i=k-r}^p |\tilde{z}_i| \geq |\tilde{z}_{k-r}|.$$

Define  $I_2 = \{1, 2, \dots, k-r-1\}$ ,  $I_1 = \{k-r, k-r+1, \dots, s\}$ , and  $I_0 = \{s+1, s+2, \dots, p\}$ ; and let  $\tilde{z}_I$  denote the vector  $\tilde{z}$  restricted to indices in  $I$ . Then the sub-differential of the vector  $k$ -support norm denoted by  $\|\cdot\|_{vk\text{-sp}}$  at  $w$  is given by:

$$\partial \|z\|_{vk\text{-sp}} = \frac{1}{\|z\|_{vk\text{-sp}}} \left\{ \tilde{z}_{I_2} + \frac{1}{r+1} \|\tilde{z}_{I_1}\|_1 (\text{sign}(\tilde{z}_{I_1}) + h_{I_0}) : \|h\|_{\infty} \leq 1 \right\},$$

**Lemma 15** (Theorem 2 in Watson (1992)). *Let  $\mathcal{R} : \mathbb{R}^{d_1 \times d_2} \rightarrow \mathbb{R}_+$  be an orthogonally invariant norm; i.e.  $\mathcal{R}(X) = \phi(\sigma(X))$  such that  $\phi : \mathbb{R}^{d_1} \rightarrow \mathbb{R}_+$  is a symmetric gauge function satisfying: (a)  $\phi(x) > 0 \forall x \neq 0$ , (b)  $\phi(\alpha x) = |\alpha| \phi(x)$ , (c)  $\phi(x+y) \leq \phi(x) + \phi(y)$ , and (d)  $\phi(x) = \phi(|x|)$ .*

*Further let  $\partial\phi(x)$  denote the sub-differential of  $\phi$  at  $x$ . Then for  $X \in \mathbb{R}^{\bar{d} \times \bar{d}}$  with singular value decomposition (SVD)  $X = U_X \Sigma_X V_X^\top$  and  $\sigma_X = \text{diag}(\Sigma_X)$ , the sub-differential of  $\mathcal{R}(X)$  is given by:*

$$\partial \mathcal{R}(X) = \{U_X D V_X^\top : D = \text{diag}(d), \text{ and } d \in \partial\Phi(\sigma_X)\}.$$

Since spectral  $k$ -support norm of a matrix  $X = U_X \Sigma_X V_X^\top$  is the vector  $k$ -support norm applied to the singular values  $\sigma_X = \text{diag}(\Sigma_X)$ , Lemma 14 and 15 can be used to infer the following:

$$\partial \|X\|_{k\text{-sp}} = \left\{ U_X D V_X^\top : \text{diag}(D) \in \frac{1}{\|\sigma_X\|_{vk\text{-sp}}} \left\{ \sigma_{X_{I_2}} + \frac{\|\sigma_{X_{I_1}}\|_1}{r+1} (\mathbf{1}_{I_1} + h_{I_0}) : \|h\|_\infty \leq 1 \right\} \right\}. \quad (31)$$

where  $\mathbf{1} \in \mathbb{R}^{\bar{d}}$  denotes a vector of all ones.

The error cone for  $\mathcal{R}(\cdot) = \|\cdot\|_{k\text{-sp}}$  is given by the tangent cone:

$$\mathcal{T}_{\mathcal{R}} = \text{cone}\{\Delta : \|\Theta^* + \Delta\|_{k\text{-sp}} \leq \|\Theta^*\|_{k\text{-sp}}\},$$

and the polar of the tangent cone – the *normal cone* is given by

$$\mathcal{T}_{\mathcal{R}}^* = \mathcal{N}_{\mathcal{R}}(\Theta^*) = \{Y : \langle Y, X \rangle \leq 0 \ \forall X \in \mathcal{T}_{\mathcal{R}}\} = \text{cone}(\partial \mathcal{R}(\Theta^*))$$

Let  $\Theta^* = U^* \Sigma^* V^{*\top}$  be the full SVD of  $\Theta^*$ , such that  $\sigma^* = \text{diag}(\Sigma^*) \in \mathbb{R}^{\bar{d}}$  and  $\sigma_1^* \geq \sigma_2^* \dots \geq \sigma_{\bar{d}}^*$ . Let  $u_i^*$  and  $v_i^*$  for  $i \in [\bar{d}]$  denote the  $i^{\text{th}}$  column of  $U^*$  and  $V^*$ , respectively. Further, let the rank of  $\Theta^*$  be  $\text{rk}(\Theta^*) = \|\sigma^*\|_0 = s$ .

Like for the vector case, denote  $r \in \{0, 1, 2, \dots, k-1\}$  to be the unique integer satisfying  $\sigma_{k-r-1}^* > \frac{1}{r+1} \sum_{i=k-r}^p \sigma_i^* \geq \sigma_{k-r}^*$ . Define  $I_2 = \{1, 2, \dots, k-r-1\}$ ,  $I_1 = \{k-r, k-r+1, \dots, s\}$ , and  $I_0 = \{s+1, s+2, \dots, p\}$ ; Also define the subspace:

$$T = \text{span}\{u_i^* x^\top : i \in I_2 \cup I_1, x \in \mathbb{R}^{\bar{d}}\} \cup \text{span}\{y v_i^{*\top} : i \in I_2 \cup I_1, y \in \mathbb{R}^{\bar{d}}\}$$

Let  $T^\perp$  be the subspace orthogonal to  $T$  and let  $P_T$  and  $P_{T^\perp}$  be the projection operators onto  $T$  and  $T^\perp$ , respectively. From (31) we have,

$$\mathcal{N}_{\mathcal{R}}(\Theta^*) = \left\{ Y = U^* D V^{*\top} : D = \text{diag}\left(t \frac{r+1}{\|\sigma_{I_1}^*\|_1} \sigma_{I_2}^* + t \mathbf{1}_{I_1} + t h_{I_0}\right) : t \geq 0, \|h\|_\infty \leq 1 \right\},$$

Finally, from Lemma 21, we have that

$$\begin{aligned} w_G^2(\mathcal{T}_{\mathcal{R}} \cap \mathbb{S}^{\bar{d}\bar{d}-1}) &\leq \mathbb{E}_G \inf_{X \in \mathcal{N}_{\mathcal{R}}(\Theta^*)} \|G - X\|_F^2 \\ &\leq \mathbb{E}_G \inf_{\substack{t > 0 \\ \|h\|_\infty \leq 1}} \left\| P_T(G) - t \frac{r+1}{\|\sigma_{I_1}^*\|_1} \sum_{i \in I_2} \sigma_i^* u_i^* v_i^{*\top} + t \sum_{i \in I_1} u_i^* v_i^{*\top} + P_{T^\perp}(G) - t \sum_{i \in I_0} h_i u_i^* v_i^{*\top} \right\|_F^2 \end{aligned}$$

Let  $P_{T^\perp}(G) = \sum_{i \in I_0} \sigma_i(P_{T^\perp}(G)) u_i^* v_i^{*\top}$  be the decomposition of  $P_{T^\perp}(G)$  in the basis of  $\{u_i^* v_i^{*\top}\}_{i \in I_0}$ . Taking  $t = \|P_{T^\perp}(G)\|_{\text{op}} = \max_{i \in I_0} \sigma_i(P_{T^\perp}(G))$ , and  $h_i = \sigma_i(P_{T^\perp}(G)) / \|P_{T^\perp}(G)\|_{\text{op}} \leq 1$ , we have:

$$w_G^2(\mathcal{T}_{\mathcal{R}} \cap \mathbb{S}^{\bar{d}\bar{d}-1}) \leq \mathbb{E}_G \|P_T(G)\|_F^2 + \left( \frac{(r+1)^2 \|\sigma_{I_2}^*\|_2^2}{\|\sigma_{I_1}^*\|_1^2} + |I_1| \right) \mathbb{E}_G \|P_T(G)\|_2^2. \quad (32)$$

Lemma 3 follows by using  $\mathbb{E}_G \|P_T(G)\|_F^2 = s(2\bar{d} - s)$  and  $\mathbb{E}_G \|P_T(G)\|_{\text{op}}^2 \leq 2(2\bar{d} - s)$  from Chandrasekaran et al. (2012).

## Appendix D. Preliminaries

### D.1 Probability and Concentration

**Lemma 16** (Bernstein's Inequality (moment version)). *Let  $X_i, i = 1, 2, \dots, N$  be independent zero mean random variables. Further, let  $\sigma^2 = \sum_i \mathbb{E}[X_i^2]$ , and  $M > 0$  be such that the following moment conditions are satisfied for  $p \geq 2$ ,*

$$\mathbb{E}[X_i^p] \leq \frac{p! \sigma^2 M^{p-2}}{2}$$

*Then the following concentration inequality holds:*

$$\mathbb{P}\left(\left|\sum_i X_i\right| > u\right) \leq 2 \exp\left(\frac{-u^2}{2\sigma^2 + 2Mu}\right) \quad (33)$$

**Lemma 17** (McDiarmid's Inequality). *Let  $X_i, i = 1, 2, \dots, N$  be independent random variables. Consider a function  $f : \mathbb{R}^N \rightarrow \mathbb{R}$ :*

$$\text{If } \forall i, \sup_{X_1, X_2, \dots, X_N, X'_i} |f(X_1, X_2, \dots, X_N) - f(X_1, X_2, \dots, X_{i-1}, X'_i, X_{i+1}, \dots, X_N)| \leq c_i,$$

$$\text{then, } \mathbb{P}(|f(X_1, X_2, \dots, X_N) - \mathbb{E}f(X_1, X_2, \dots, X_N)| > u) \leq 2 \exp\left(\frac{-2u^2}{\sum_i c_i^2}\right) \quad (34)$$

**Lemma 18** (Symmetrization (Lemma 6.3 in Ledoux and Talagrand (1991))). *Let  $F : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  be a convex function, and  $X_i, i = 1, 2, \dots$  be a sequence of mean zero random variables in a Banach space  $B$ , s.t  $\forall i, \mathbb{E}F\|X_i\| < \infty$ . Denote a vector of standard Rademacher variables of appropriate dimension as  $(\epsilon_i)$ , then*

$$\mathbb{E}F\left(\frac{1}{2}\left\|\sum_i \epsilon_i X_i\right\|\right) \leq \mathbb{E}F\left\|\sum_i X_i\right\| \leq \mathbb{E}F\left(2\left\|\sum_i \epsilon_i X_i\right\|\right) \quad (35)$$

*Further, if  $X_i$  are not centered, then  $\mathbb{E}F\left(\left\|\sum_i X_i - \mathbb{E}[X_i]\right\|\right) \leq \mathbb{E}F\left(2\left\|\sum_i \epsilon_i X_i\right\|\right)$*

**Lemma 19** (Contraction Principle). *Consider a bounded  $T \subset \mathbb{R}^N$ , a standard Gaussian and standard Rademacher sequence,  $(g_i) \in \mathbb{R}^N$  and  $(\epsilon_i) \in \mathbb{R}^N$ , respectively. If  $\phi_i : \mathbb{R} \rightarrow \mathbb{R}, i \leq N$  are contractions, i.e.  $\forall s, t \in \mathbb{R}, |\phi_i(s) - \phi_i(t)| \leq |s - t|$ , and with  $\phi_i(0) = 0$ , then for any convex function  $F : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ , the following results are from Corollary 3.17, Theorem 4.12, and Lemma 4.5, respectively in Ledoux and Talagrand (1991):*

$$\mathbb{E}F\left(\frac{1}{2} \sup_{t \in T} \left|\sum_{i=1}^N g_i \phi_i(t_i)\right|\right) \leq \mathbb{E}F\left(2 \sup_{t \in T} \left|\sum_{i=1}^N g_i t_i\right|\right) \quad (36)$$

$$\mathbb{E}F\left(\frac{1}{2} \sup_{t \in T} \left|\sum_{i=1}^N \epsilon_i \phi_i(t_i)\right|\right) \leq \mathbb{E}F\left(2 \sup_{t \in T} \left|\sum_{i=1}^N \epsilon_i t_i\right|\right) \quad (37)$$

$$\mathbb{E}F\left(\left\|\sum_{i=1}^N \epsilon_i t_i\right\|\right) \leq \mathbb{E}F\left(\sqrt{\frac{\pi}{2}} \left\|\sum_{i=1}^N g_i t_i\right\|\right) \quad (38)$$

## D.2 Gaussian Width

Gaussian width plays a key role in high dimensional estimation, and plenty of tools have been developed for computing Gaussian widths of compact subsets (Dudley, 1967; Ledoux and Talagrand, 1991; Talagrand, 2014; Chandrasekaran et al., 2012). The existing work is specially well adapted for computing Gaussian widths for intersection of convex cones with unit norm balls (Chandrasekaran et al., 2012), and recent work of Banerjee et al. (2014) propose a mechanism for exploiting these tools for arbitrary compact sets. We briefly note some of the key results that aid in computing Gaussian widths. Recall that  $\mathbb{S}^{d_1 d_2 - 1}$  is a unit Euclidean sphere in  $\mathbb{R}^{d_1 \times d_2}$ . Further, for a cone  $\mathcal{C} \in \mathbb{R}^{d_1 \times d_2}$ , we define the polar cone as  $\mathcal{C}^\circ = \{X : \langle X, Y \rangle \leq 0, \forall Y \in \mathcal{C}\}$ .

### D.2.1 DIRECT ESTIMATION

The Gaussian width of a compact set  $T$  can be directly estimated as a supremum of Gaussian process over dense countable subset  $\bar{T}$  of  $T$  as  $w_G(T) = \sup_{X \in \bar{T}} \langle X, G \rangle$ .

We state the following properties are often used in direct estimation. These properties are consolidated from Talagrand (2014), Chandrasekaran et al. (2012) and Banerjee et al. (2014). In the following statements,  $k$  is a constant not necessarily the same in each occurrence:

- Translation invariant and homogeneous: for any  $a \in \mathbb{R}$ ,  $w_G(S + a) = w_G(S)$ ; and .
- $w_G(\text{conv}(T)) \leq w_G(T)$
- $w_G(T_1 + T_2) \leq w_G(T_1) + w_G(T_2)$
- If  $T_1 \subseteq T_2$ , then  $w_G(T_1) \leq w_G(T_2)$ .
- If  $T_1$  and  $T_2$  are convex, then  $w_G(T_1 \cup T_2) + w_G(T_1 \cap T_2) = w_G(T_1) + w_G(T_2)$

### D.2.2 DUDLEY'S INEQUALITY AND SUDAKOV MINORIZATION

**Definition 8** (Covering Number). Consider a metric  $d$  defined on  $S \subset \mathbb{R}^{d_1 \times d_2}$ . Given  $\epsilon > 0$ , the  $\epsilon$ -covering number of  $S$  with respect to  $d$ , denoted by  $\mathcal{N}(S, \epsilon, d)$ , is the minimum number of points  $\{\bar{X}_1, \bar{X}_2, \dots, \bar{X}_{\mathcal{N}(S, \epsilon, d)}\}$  such that  $\forall X \in S$ , there exists  $i \in \{1, 2, \dots, \mathcal{N}(S, \epsilon, d)\}$  with  $d(X, \bar{X}_i) \leq \epsilon$ . The set  $\{\bar{X}_1, \bar{X}_2, \dots, \bar{X}_{\mathcal{N}(S, \epsilon, d)}\}$  is called the  $\epsilon$ -cover of  $S$ .

**Lemma 20** (Dudley's Inequality and Sudakov Minoration). *If  $S$  is compact, then for any  $\epsilon > 0$ , there exists a constant  $c$  s. t.*

$$c\epsilon \sqrt{\log N(S, \epsilon, \|\cdot\|_F)} \leq w_G(S) \leq 24 \int_0^\infty \sqrt{N(S, \epsilon, \|\cdot\|_F)} d\epsilon.$$

*The upper bound is the Dudley's inequality and lower bound is by Sudakov minoration.*

### D.2.3 GEOMETRY OF POLAR CONE

**Lemma 21** (Proposition 3.6 and Theorem 3.9 of Chandrasekaran et al. (2012)). *If  $\mathcal{C} \subset \mathbb{R}^{d_1 \times d_2}$  is a non-empty convex cone and  $\mathcal{C}^\circ$  be its polar cone, then:*

$$\text{Distance to polar cone} : w_G(\mathcal{C} \cap \mathbb{S}^{d_1 d_2 - 1}) \leq \mathbb{E}_G[\inf_{X \in \mathcal{C}^\circ} \|G - X\|_F]$$

$$\text{Volume of polar cone} : w_G(\mathcal{C} \cap \mathbb{S}^{d_1 d_2 - 1}) \leq 3 \sqrt{\frac{4}{\text{vol}(\mathcal{C}^\circ \cap \mathbb{S}^{d_1 d_2 - 1})}}$$

#### D.2.4 INFIMUM OVER TRANSLATED CONES

**Lemma 22** (Lemma 3 of Banerjee et al. (2014)). *Let  $S \subset \mathbb{R}^{d_1 \times d_2}$ , and given  $X \in S$ , define  $\rho(X) = \sup_{Y \in S} \|X - Y\|_F$  as the diameter of  $S$  measured along  $X$ . Also define  $\mathcal{G}(X) = \text{cone}(S - X) \cap \rho(X)\mathbb{B}^{d_1 d_2}$ , where  $\mathbb{B}^{d_1 d_2}$  is the unit Euclidean ball. Then,*

$$w_G(S) \leq \inf_{X \in S} w_G(\mathcal{G}(X))$$

#### D.2.5 GENERIC CHAINING

Lemma 10 (from Talagrand (2014)) gives the tightest bounds on the Gaussian width of a set. The definition of  $\gamma_2$  (23) can be used to derive tight bounds on the Gaussian width that are optimal up to constants. Further results and examples on using  $\gamma$ -functionals for Gaussian width computation can be found in the works of Talagrand (Talagrand, 1996, 2001, 2014).

### D.3 Sub-Gaussian and Sub-Exponential Random Variables

Recall the definition of sub-Gaussian random variables from Definition 2.

**Definition 9** (Sub-Exponential Random Variables). A random variable  $X$  is said to be *sub-exponential* if it satisfies one of the following equivalent conditions for  $k_1$ ,  $k_2$ , and  $k_3$  differing from one other by constants [Definition 5.13 of Vershynin (2012)].

1.  $\mathbb{P}(|X| > t) \leq e^{1-t/k_1}, \forall t > 0$ ,
2.  $\forall p \geq 1, (\mathbb{E}[|X|^p])^{1/p} \leq k_2 p$ , or
3.  $\mathbb{E}[e^{X/k_3}] \leq e$ .

The *sub-exponential norm* is given by:

$$\|X\|_{\Psi_1} = \inf \left\{ t > 0 : \mathbb{E} \exp \left( \frac{|X|}{t} \right) \leq 2 \right\} = \sup_{p \geq 1} p^{-1} (\mathbb{E}[|X|^p])^{1/p}. \quad (39)$$

The following results on sub-Gaussian and sub-exponential variables are from Vershynin (2012).

**Lemma 23** (Hoeffding-type inequality, Proposition 5.10 in Vershynin (2012)). *Let  $X_1, X_2, \dots, X_N$  be independent centered sub-Gaussian random variables, and let  $K = \max_i \|X_i\|_{\Psi_2}$ . Then,  $\forall a \in \mathbb{R}^N$  and  $t \geq 0$ ,  $\exists$  constant  $c$  s.t.,*

$$\mathbb{P} \left( \left| \sum_{i=1}^N a_i X_i \right| \geq t \right) \leq 2 \exp \left( \frac{-ct^2}{K^2 \|a\|_2^2} \right). \quad (40)$$

**Lemma 24** (Bernstein-type inequality, Proposition 5.16 in Vershynin (2012)). *Let  $X_1, X_2, \dots, X_N$  be independent centered sub-exponential random variables, and let  $K = \max_i \|X_i\|_{\Psi_1}$ . Then  $\forall a \in \mathbb{R}^N$ , and  $t \geq 0$ , there exists a constant  $c$  s.t.*

$$\mathbb{P} \left( \left| \sum_{i=1}^N a_i X_i \right| \geq t \right) \leq 2 \exp \left( -c \min \left\{ \frac{t^2}{K^2 \|a\|_2^2}, \frac{t}{K \|a\|_\infty} \right\} \right). \quad (41)$$

**Lemma 25** (Lemma 5.14 in Vershynin (2012)).  *$X$  is sub-Gaussian if and only if  $X^2$  is sub-exponential. Further,  $\|X\|_{\Psi_2}^2 \leq \|X^2\|_{\Psi_1} \leq 2\|X\|_{\Psi_2}^2$ .*

**Lemma 26** (Remark 5.18 in Vershynin (2012)). *If  $X$  is sub-Gaussian (or sub-exponential), then so is  $X - \mathbb{E}X$ . Further,  $\|X - \mathbb{E}X\|_{\Psi_2} \leq 2\|X\|_{\Psi_2}$ ;  $\|X - \mathbb{E}X\|_{\Psi_1} \leq 2\|X\|_{\Psi_1}$ .*

## Appendix E. Extension to GLMs

This section provides directions for extending the work to matrix completion under generalized linear models. This section has not been rigorously formalized. An accurate version will be included in a longer version of the paper.

We consider an observation model wherein the observation matrix  $Y$  is drawn from a member of *natural exponential family* parametrized by a structured ground truth matrix  $\Theta^*$ , such that:

$$P(Y|\Theta^*) = \prod_{ij} p(Y_{ij}) e^{Y_{ij}\Theta_{ij}^* - A(\Theta_{ij}^*)}, \quad (42)$$

where  $A : \text{dom}(\Theta_{ij}) \rightarrow \mathbb{R}$  is called the *log-partition function* and is strictly convex and analytic, and  $p(\cdot)$  is called the *base measure*. This family of distributions encompass a wide range of common distributions including Gaussian, Bernoulli, binomial, Poisson, and exponential among others. In a generalized linear matrix completion setting (Gunasekar et al., 2014), the task is to estimate  $\Theta^*$  from a subset of entries  $\Omega$  of  $Y$ , i.e.  $(\Omega, P_\Omega(Y))$ .

A useful consequence of exponential family distribution assumption for observation matrix is that the negative log-likelihood loss over the observed entries is convex with respect to the natural parameter  $\Theta^*$ , and have a one-to-one correspondence with a rich class of divergence functions called the Bregman Divergence (Forster and Warmuth, 2002; Banerjee et al., 2005). The negative log likelihood is proportional to:

$$\mathcal{L}_\Omega(\Theta) = \sum_{(i,j) \in \Omega} A(\Theta_{ij}) - Y_{ij}\Theta_{ij}$$

We propose the following *regularized matrix estimator* for generalized matrix completion:

$$\hat{\Theta}_{re} = \underset{\|\Theta\|_\infty \leq \frac{\alpha^*}{\sqrt{d_1 d_2}}}{\text{argmin}} \frac{d_1 d_2}{|\Omega|} \mathcal{L}_\Omega(\Theta) + \lambda_{re} \mathcal{R}(\Theta). \quad (43)$$

**Hypothesis 1.** Let  $\hat{\Theta}_{re} = \Theta^* + \hat{\Delta}_{re}$ . In addition to the assumptions in Section 2, we assume that for some  $\eta \geq 0$ ,  $\nabla^2 A(u) \geq e^{-\eta|u|} \forall u \in \mathbb{R}$ . The following result holds for any fixed  $\gamma > 1$ . We define:

$$\tilde{\mathcal{T}}_{\mathcal{R},\gamma} = \text{cone}\{\Delta : \mathcal{R}(\Theta^* + \Delta) \leq \mathcal{R}(\Theta^*) + \frac{1}{\gamma} \mathcal{R}(\Theta^*)\}, \quad \text{and} \quad \tilde{\mathcal{E}}_{\mathcal{R},\gamma} = \tilde{\mathcal{T}}_{\mathcal{R},\gamma} \cap \mathbb{S}^{d_1 d_2 - 1}. \quad (44)$$

Let  $\lambda_{re} \geq \gamma \frac{d_1 d_2}{|\Omega|} \mathcal{R}^*(\nabla \mathcal{L}_\Omega(\Theta^*))$ , and for some  $c_0$ ,  $|\Omega| > \left(\frac{\gamma+1}{\gamma-1}\right)^2 c_0^2 w_G^2(\tilde{\mathcal{E}}_{\mathcal{R},\gamma}) \log d$ . There exists a constant  $k_1$  such that for large enough  $c_0$ , there exists  $\kappa_{c_0} > 0$ , such that with high probability,

$$\|\hat{\Delta}_{re}\|_F^2 \leq 4\alpha^{*2} \left(\frac{\gamma+1}{\gamma-1}\right)^2 \max \left\{ \frac{\lambda_{re}^2 \Psi_{\mathcal{R}}^2(\tilde{\mathcal{T}}_{\mathcal{R},\gamma})}{\zeta(\eta, \alpha^*) \kappa_{c_0}^2}, \frac{c_0^2 w_G^2(\tilde{\mathcal{E}}_{\mathcal{R},\gamma}) \log d}{|\Omega|} \right\},$$

where  $\zeta(\eta, \alpha^*) = e^{\frac{-4\eta\alpha^*}{\sqrt{d_1 d_2}}}$ , and  $\alpha^*$ ,  $w_G(\cdot)$ , and  $\Psi_{\mathcal{R}}(\cdot)$  are notations from Section 3.

The conjectures follows by combining the results in this paper along with the results from Banerjee et al. (2014), and Gunasekar et al. (2014). This result is beyond the scope of this paper and will be dealt with more rigorously in a longer version of the paper.